Neural Computation

NEUR 416 / CAAM 416 / ELEC 489 / ELEC 589

1. Course Summary

How does the brain work? Understanding the brain requires sophisticated theories to make sense of the collective actions of billions of neurons and trillions of synapses. Word theories are not enough; we need mathematical theories. The goal of this course is to provide an introduction to the mathematical theories of learning and computation by neural systems. These theories use concepts from dynamical systems (attractors, chaos) and concepts from statistics (information, uncertainty, inference) to relate the dynamics and function of neural networks. We will apply these theories to sensory computation, learning and memory, and motor control. Our learning objectives are for you to formalize and mathematically answer questions about neural computations including "what does a network compute?", "how does it compute?", and "why does it compute that way?"

2. Instructors:

Xaq Pitkow, Baylor College of Medicine & Rice University; xaq@rice.edu.
Lokesh Boominathan (Teaching Assistant), Rice University; lb36@rice.edu.
Office hours to be determined for Xaq and Lokesh.

3. Course Description

Tuesdays and Thursdays, 3:10-4:30 pm
Location: ***online only***
Recommended textbook: *Theoretical Neuroscience*, by Dayan and Abbott

Audience: Graduate and undergraduate students with quantitative training and interests in theories of how the brain works.
Prerequisites: calculus, linear algebra, probability and statistics, some programming experience
3 credits, Elective

4. Grading Criteria: homework (45%), quizzes (5%), two exams (15% each), and final project (20%).

Homeworks turned in late without pre-approved justification will lose 5% per day.

Several short quizzes (**Concept Questions**) must be completed before class, to get us started thinking about certain ideas. These do not require mathematical computation but rather emphasize conceptual reasoning.

Midterms will be 3-hour take-home exams. You may use your notes, lecture notes, and readings, but no internet.

Final projects will have a 10-minute presentation (50%) and a written report (50%, ~6–10 pages).
The topic of your final projects is flexible. Examples include:

- Reproducing and slightly extending results in a theory or modeling paper
- Analyzing real or simulated data in context of a theory
- Quantitatively contrasting or critiquing competing theories
- Interactive visualization of an interesting theoretical concept
- Historical review of a core theoretical idea

Undergraduates may work in pairs if desired. Individual contributions should be documented. Graduate students taking ELEC 589 are expected to work alone on projects, and to have more comprehensive results (~10 pages for grads, versus ~6 pages for undergrads).

Date	Content	Reading (DA = Dayan and Abbott)	Assignment
26jan	Introduction Goals of neural computation		HW1: fun with gaussians and information (due 2feb)
28jan	Workshop on computational neuroscience, 10:00–3:00 **REGISTER:** https://www.gulfcoastconsortia.org/event/neuronox-workshop/ https://uofh.zoom.us/j/97694246773?pwd=d0RTdS9qWk5XalA4ZHFUNzNpNTh5dz09 Meeting ID: 976 9424 6773 Passcode: 496298		
28jan	Efficient coding 1		HW2: efficient coding (due 9feb)
29jan (FRI)	Theoretical and Computational Neuroscience Symposium, 9:00–5:00 **REGISTER:** *https://www.eventbrite.com/e/18th-annual-theoretical-and-computational-neuroscience-virtual-conference-tickets-117762427591*		
2feb	Efficient coding 2	DA 4.1–4.2, appendix on Fourier Transforms van Hateren 1992	
4feb	Population codes: *encoding* (tuning curves, receptive fields)	DA 1.1–1.3 DA 3.1–3.3	HW3: population codes (due 16feb)
9feb	*decoding* (estimation, discrimination, action)		
11feb	Feedforward networks (1 layer, perceptrons)	DiCarlo and Cox 2007	HW4: feedforward nets (due 23feb)
16feb	Learning in networks: perceptron learning rule, Hebbian plasticity, backpropagation	DA 8.1–8.2, 8.4	
18feb	Multilayer nonlinear feedforward networks: *recoding* Object recognition by deep networks	Bishop 9.2	Project preparation
23feb	Linear recurrent networks (deterministic)	DA 7.4, up to linear recurrent networks. Appendix: Linear Algebra, Differential equations	
24–26feb	Cosyne (Computational and Systems Neuroscience conference) cosyne.org		
25feb	Univariate stochastic linear dynamics	Scholarpedia: Stochastic dynamical systems	HW5: linear recurrent networks (due 2mar)

2mar	Multivariate stochastic linear recurrent networks Kalman filter, line attractors, integrators	How a Kalman Filter works, in pictures. Gold and Shadlen 2001	Exam I open (due FRI 5mar)
4mar	Balanced networks, chaos	DA 7.5, 10.1–10.2	
9mar	Nonlinear dynamics 1 Reduction techniques and stochastic nonlinear models (bursters, reduced line attractor models, Takens' theorem)	Strogatz Ch 1 Wilson and Cowen 1972 DA 7.4 from Nonlinear recurrent networks, DA 7.5	
11mar	Nonlinear dynamics 2 Recurrent networks (continuous attractor, ring model)		HW6: nonlinear dynamics (due WED 17mar)
16mar	NO CLASS		
18mar	Project check-in		
23mar	Associative memory: Hopfield network (discrete attractor)	DA 7.4: Associative Memory. Hopfield 1982	
25mar	Boltzmann machine (probabilistic computation, unsupervised learning)	DA 7.6; 8.4: "contrastive Hebbian learning" Ackley 1983	HW7: Hopfield net (due 30mar)
30mar	Probabilistic population codes	Ma et al 2006 Berkes et al 2007	
1apr	Causal inference	Bishop 8.2–8.3	HW8: Boltzmann machine (due 6apr)
6apr	Motor control	Shenoy et al 2013	HW9: Motor control (due 13apr)
8apr	Reinforcement learning	DA 9	
13apr	Context dependent computation	Mante et al 2012	
15apr	Catchup time		Exam II open (due 19apr)
20apr	Deep thoughts: consciousness and free will	The strong free will theorem Conway & Kochen 2009	Written projects (due 30 apr)
22apr	Project presentations		
27apr	Project presentations		
29apr	Project presentations		